Clustering Reviewers to Predict Movie Ratings

Dataset(s)

I used the IMDB Movie Datasets. Specifically, I used the ratings and movies datasets.

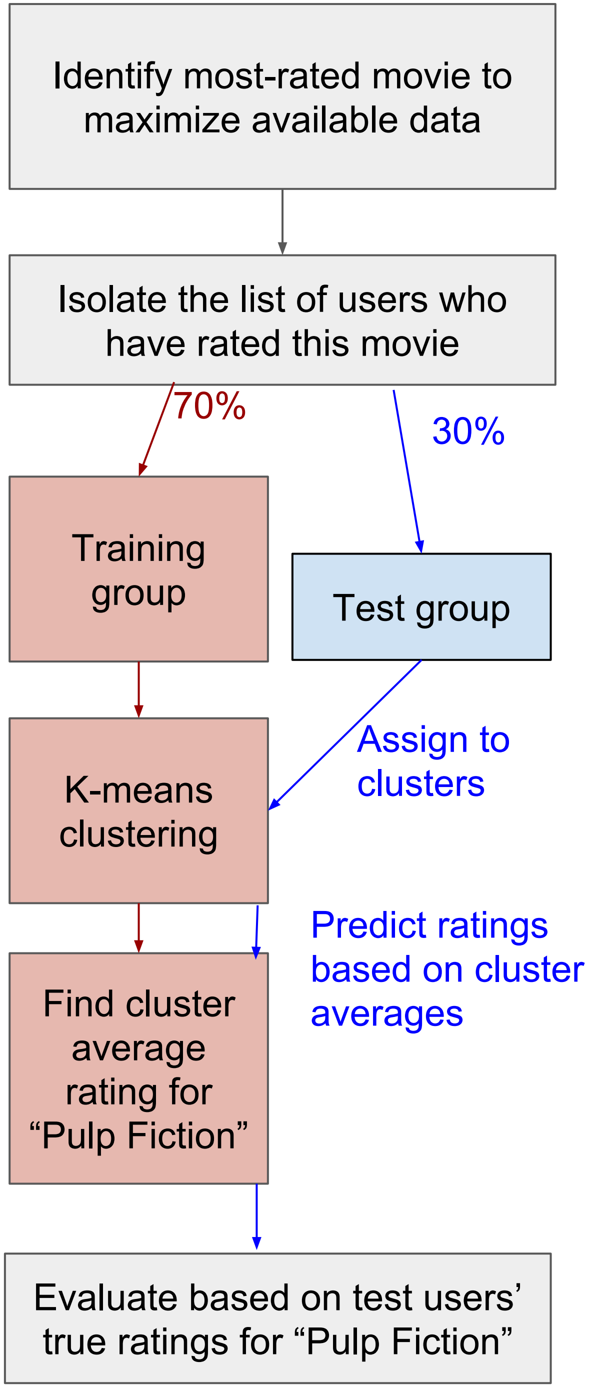
Motivation

Movie streaming or rental services frequently give recommendations based on what its subscribers have previously watched and reviewed. It is likely that the more accurately a movie service can do this, the more satisfied its customers will be, so creating a method that can accurately predict how much a customer would enjoy a particular movie is likely very valuable.

Research Question

Can I predict a user's rating for a movie by comparing them to other users with similar interests? I hypothesized that I could use a customer's other reviews to predict their rating for a movie, "Pulp Fiction."

To do this, I clustered some users (the training group) based on their average ratings for each genre of the data set and calculated the average rating of "Pulp Fiction" for each cluster (the cluster average). Then, I put other users into these clusters and used the cluster average to predict their rating for "Pulp Fiction."



Identify most-rated movie to maximize available data
Isolate the list of users who have rated this movie
70%
30%
Training group
Test group
K-means clustering
Assign to clusters
Predict ratings based on cluster averages
Find cluster average rating for "Pulp Fiction"
Evaluate based on test users' true ratings for "Pulp Fiction"

Findings

I found that “Pulp Fiction” is the most-rated movie in the dataset, with 67,310 reviews (representing 48% of all reviewers).

Using K-means clustering, I created 100 clusters of the 47,117 users in my training set (Fig 1 and 2)

Some clusters appeared to be harsh critics, rating everything fairly poorly, while other clusters had high average ratings across genres. For users who had no reviews in a particular genre, I assigned their average rating to that genre to be 0 based on the assumption that users likely do not watch movies in genres that they dislike. It seems that many users do not watch certain genres, such as documentary or film-noir, as evidenced by near-zero ratings. (Fig 2)

“Pulp Fiction” spans multiple genres, including comedy, crime, drama, and thriller.

Fig 1

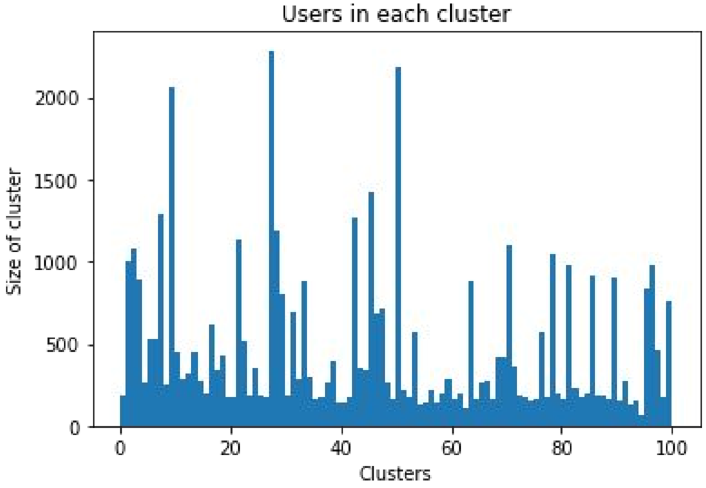
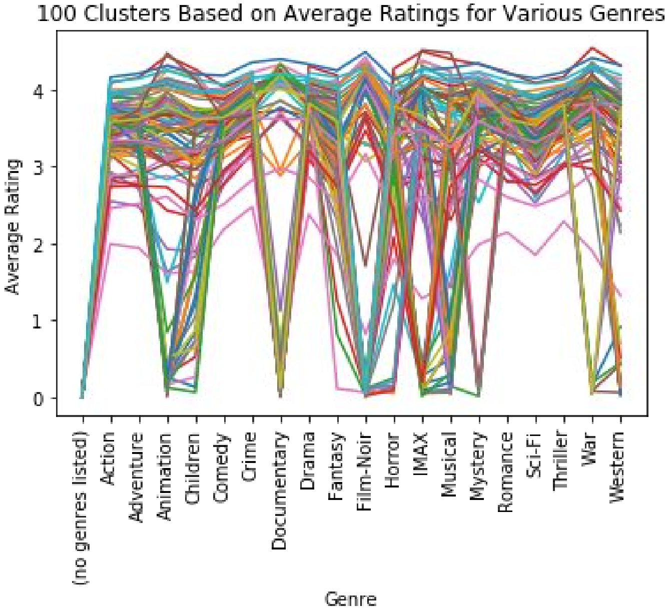


Fig 2



Findings

After assigning users in my test set to clusters, I predicted that their rating would be the cluster's average rating for "Pulp Fiction." Cluster averages ranged from 3.22 to 4.71. As a control, non-personalized prediction, I used the average rating of all users for "Pulp Fiction (4.17). A sample of the cluster assignments, predicted ratings, true ratings, and non-personalized rating prediction can be seen in Fig 3.

The root mean squared error was about 3% better for my personalized predictions (0.95) compared to the non-personalized predictions (0.98), **suggesting that this approach is somewhat successful.**

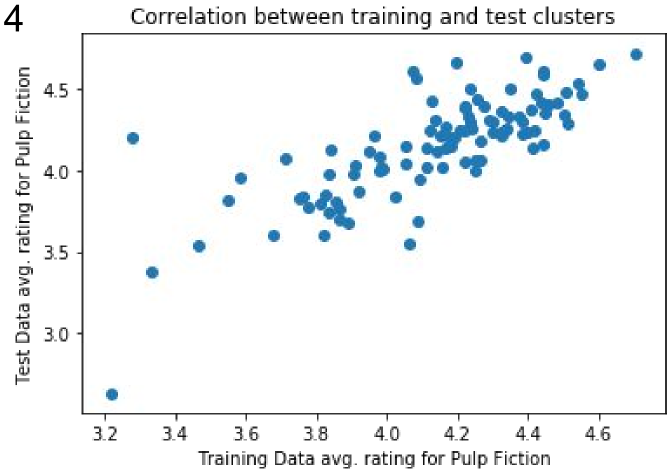
Within the clusters, the true ratings for "Pulp Fiction" were well-correlated between the test and training groups, which suggests that the clusters are meaningful (Fig 4).

Fig 3

Cluster assignments, predictions and true rating for 5 sample users

cluster	ratingPredict	rating	defaultPredict
46	3.463693	3.0	4.173706
64	4.083333	5.0	4.173706
28	4.053790	4.5	4.173706
2	3.774834	1.0	4.173706
70	4.705311	5.0	4.173706

Fig 4



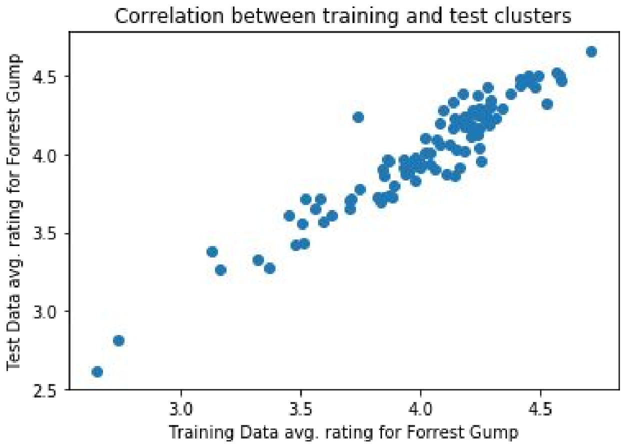
Findings

As an extension, I experimented with different cluster sizes. I found that when using 8 clusters, I only improved the root mean squared error by about 1.5%. When I tried to use 500 clusters, I found that the runtime for clustering was too slow.

I also tested my algorithm for the next most-rated movie, “Forrest Gump.” **I achieved a 6.7% improvement in root mean squared error for that movie**, with even better correlation between the ratings in my test and training sets.

Both “Pulp Fiction” and “Forrest Gump” are classics with overall very high reviews, so future work could test the method on more polarizing movies.

Fig 5



Acknowledgements

I decided to use K-means clustering after seeing the example of it in the Soccer Analysis notebook from the first week of the course.

My husband helped me debug my notebook and gave me feedback on the size of training/test groups and the root mean squared error calculation.

References

I used documentation on the following websites to determine syntax and debug my code.

- pandas.pydata.org
- docs.python.org
- stackoverflow.com

Overview

Goal: Can we predict a user's rating for a movie better than by giving the average rating?

Method:

1. Find the most-rated movie (to maximize the data)
2. Isolate the list of users who have rated this movie
3. Split this user list into a training/test group
4. Cluster users based on their ratings for other movies and find the average rating for the most-rated movie for each cluster
5. Determine where the test users fit in these clusters, predict that their rating for the movie will be the average of their cluster
6. Compare these predicted ratings vs. their true rating to the default prediction vs. true rating (the default prediction is that all users would rate it as the total average rating for that movie)

In [137]:

```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
%matplotlib inline
import matplotlib.pyplot as plt

movies = pd.read_csv('./movielens/movies.csv', sep=',')
ratings = pd.read_csv('./movielens/ratings.csv', sep=',')
del ratings["timestamp"]
```

In [138]:

```
movies.head()
```

Out[138]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [139]:

```
ratings.head()
```

Out[139]:

	userId	movieId	rating
0	1	2	3.5
1	1	29	3.5
2	1	32	3.5
3	1	47	3.5
4	1	50	3.5

In [140]:

```
ratings["rating"].isnull().any()
```

Out[140]:

```
False
```

All of the reviews are filled in! Yay!

Step 1: Find the most-rated movie (to maximize the data)

In [141]:

```
ratingCounts=ratings["movieId"].value_counts()
ratingCounts.head()
```

Out[141]:

```
296    67310
356    66172
318    63366
593    63299
480    59715
Name: movieId, dtype: int64
```

The most-rated movie is movieId 296, with 67,310 reviews.

In [142]:

```
mId = 296
```

In [143]:

```
movies[movies["movieId"] == mId]
```

Out[143]:

	movieId	title	genres
293	296	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller

MovieId 296 is Pulp Fiction. Makes sense!

Step 2: 2. Isolate the list of users who have rated this movie

```
In [144]: ratingsOfInterest = ratings[ratings["movieId"]==mId]
          ratingsOfInterest.count()
```

```
Out[144]: userId      67310
          movieId     67310
          rating      67310
          dtype: int64
```

```
In [145]: len(ratingsOfInterest["userId"].unique().tolist())/len(ratings["userId"].
          nique().tolist())*100
```

```
Out[145]: 48.60173438368726
```

As expected, there are 67,310 reviews for this movie. 48% of all reviewers rated this movie!

```
In [146]: ratingsOfInterest.head()
```

```
Out[146]:
```

	userId	movieId	rating
11	1	296	4.0
845	8	296	5.0
983	11	296	3.5
1525	13	296	5.0
1821	15	296	3.0

```
In [147]: users = ratingsOfInterest["userId"].unique().tolist()
          len(users)
```

```
Out[147]: 67310
```

There are 67,310 users in my list, which means that no one did more than one review.

Step 3: Split this user list into a training/test group

I will break the 67,310 users into a 70-30 split

```
In [148]: trainingProp = 0.7
          testProp = 1-trainingProp

          print("training: ", int(len(users)*trainingProp))
          print("test: ", int(len(users)*testProp))

          training:  47117
          test:  20193
```

```
In [149]: import random
          random.shuffle(users)
```

```
In [150]: trainingUsers = users[:int(len(users)*trainingProp)]
          len(trainingUsers)

Out[150]: 47117
```

```
In [151]: testUsers = users[int(len(users)*trainingProp):]
          len(testUsers)

Out[151]: 20193
```

Step 4: Cluster users based on their ratings for other movies and find the average rating for the most-rated movie for each cluster

```
In [152]: # I'm adding the movie info to the ratings now for ease of use in my clu
          stering
          ratingsPlus = ratings.merge(movies, on="movieId", how = "inner")
```

```
In [153]: ratingsPlus.head()

Out[153]:
```

	userId	movieId	rating	title	genres
0	1	2	3.5	Jumanji (1995)	Adventure|Children|Fantasy
1	5	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
2	13	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
3	29	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
4	34	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy

In [154]:

```
TrainingFilter = ratingsPlus["userId"].isin(trainingUsers)
ratingsForTraining = ratingsPlus[TrainingFilter]
ratingsForTraining.head()
```

Out[154]:

	userId	movieId	rating	title	genres
0	1	2	3.5	Jumanji (1995)	Adventure|Children|Fantasy
3	29	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
4	34	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
5	54	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
7	91	2	3.5	Jumanji (1995)	Adventure|Children|Fantasy

At this point, I have all of the ratings that correspond to users in my training set. I would like to make a dataframe that I can cluster them on. I think that it will be too sparse if I make a big n x m dataframe where n is the number of users and m is the number of movies, where the (n,m) entry is user n's rating for movie m. So instead, I will make an n x l dataframe where l is the number of genres. The (n,l) entry is user n's average rating for movies containing genre l.

In [155]:

```
#Here I am extracting all the genres for each movie and putting them all
 in a list
genreLists=movies["genres"].str.split("|")
genreList = []
# make a list of all genres mentioned, with redundancy
for movieGenres in genreLists:
    genreList.extend(movieGenres)
len(genreList)
```

Out[155]:

```
54406
```

In [156]:

```
# this gets the unique list of genres by making it a set.
genreList = set(genreList)
print(genreList)
len(genreList)
```

```
{'Sci-Fi', 'Thriller', 'IMAX', 'Mystery', '(no genres listed)', 'Crim
e', 'War', 'Drama', 'Adventure', 'Documentary', 'Animation', 'Comedy',
 'Western', 'Horror', 'Children', 'Action', 'Musical', 'Fantasy', 'Film
-Noir', 'Romance'}
```

Out[156]:

```
20
```

There are 20 genres.

In [157]:

```
compute = False

# This is a really computationally intensive loop, so I will only run it if I need to.
# If compute is false, it reads it from the file instead of recomputing everything.
if compute:
    userDicts = []
    userIds = []
    for thisUser in trainingUsers:
        thisUserDict = {}
        thisUsersRatings = ratingsForTraining[ratingsForTraining["userId"] == thisUser]
        #print(thisUsersRatings[["userId", "rating", "title"]])
        for genre in genreList:
            genreFilter = thisUsersRatings["genres"].str.contains(genre)
            avgRating = thisUsersRatings[genreFilter]["rating"].mean()
            thisUserDict[genre]=avgRating
        userDicts.append(thisUserDict)
        userIds.append(thisUser)
    df = pd.DataFrame(userDicts, index = userIds)
    df.to_csv("TrainingDf.csv")
else:
    df= pd.read_csv("TrainingDf.csv", index_col = 0)
```

In [158]:

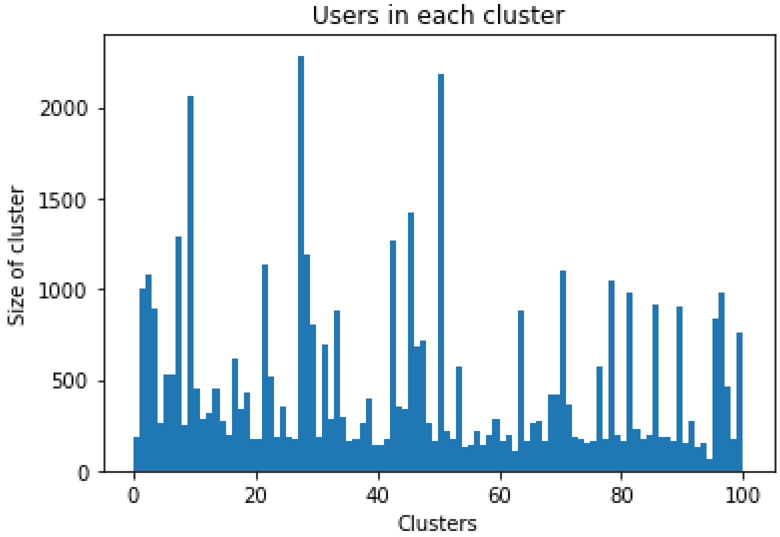
```
dfNoNan=df.replace(np.nan,0)
```

In [159]:

```
nClusters= 100
kmeans = KMeans(n_clusters=nClusters).fit(dfNoNan)
```

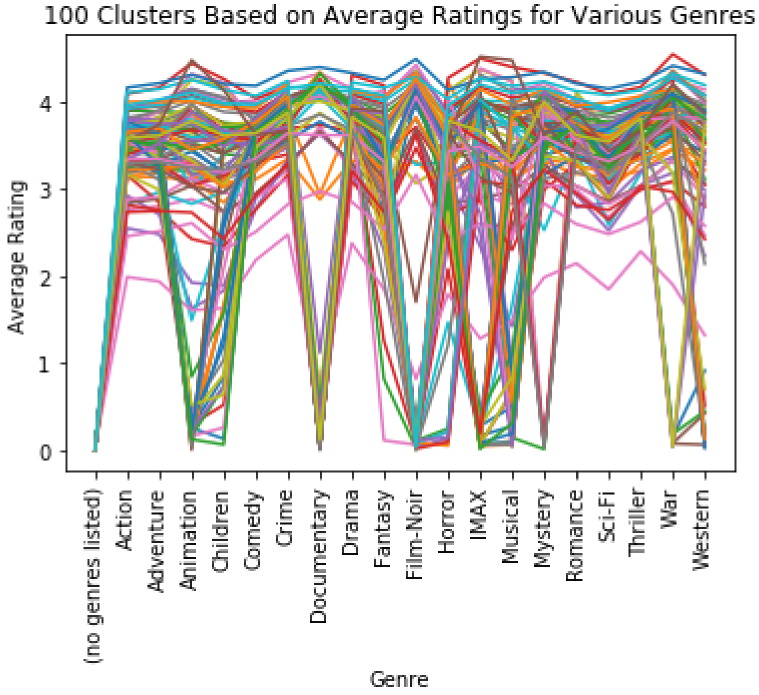
kmeans.labels_ is an array with an entry for each of my training users specifying which cluster they are in.

In [160]:
```
plt.hist(kmeans.labels_, nClusters, [0,nClusters])
plt.title("Users in each cluster")
plt.ylabel("Size of cluster")
plt.xlabel("Clusters")
plt.show()
```



In [161]:
```
fig, ax = plt.subplots()
ax.plot(kmeans.cluster_centers_.T)
ax.set_xlabel('Genre')
ax.set_ylabel('Average Rating')
ax.set_xticks(range(len(dfNoNan.columns)))
ax.set_xticklabels(dfNoNan.columns)
ax.set_xticklabels(ax.xaxis.get_ticklabels(), rotation=90)
ax.set_title("%d Clusters Based on Average Ratings for Various Genres"
%nClusters)

plt.show()
```



Some people tend to rate everything highly. Other clusters notably do not watch certain genres, such as Documentary or Film-Noir.

In [162]:

```
dfNoNan.describe()
```

Out[162]:

	(no genres listed)	Action	Adventure	Animation	Children	Cor
count	47117.000000	47117.000000	47117.000000	47117.000000	47117.000000	47117.00
mean	0.006967	3.485441	3.513823	3.290386	3.282595	3.524217
std	0.160290	0.521799	0.535808	1.238575	1.013032	0.464236
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.613636
25%	0.000000	3.176471	3.208333	3.000000	3.000000	3.244048
50%	0.000000	3.500000	3.545455	3.600000	3.500000	3.544186
75%	0.000000	3.833333	3.862745	4.000000	3.916667	3.833333
max	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000

In [163]:

```
annotatedDf=dfNoNan
annotatedDf["cluster"]=kmeans.labels_
```

In [164]:

```
userCluster = annotatedDf["cluster"]
```

In [165]:

```
pulpReviews=ratingsForTraining[["userId", "rating"]]
[ratingsForTraining["movieId"]==mId]
indexedPulpReviews = pulpReviews.set_index("userId")
```

In [166]:

```
indexedPulpReviews["cluster"]=userCluster
```

In [167]:

```
clusterPulpRatings = indexedPulpReviews[["rating",
"cluster"]].groupby("cluster").mean()
clusterPulpRatings.head()
```

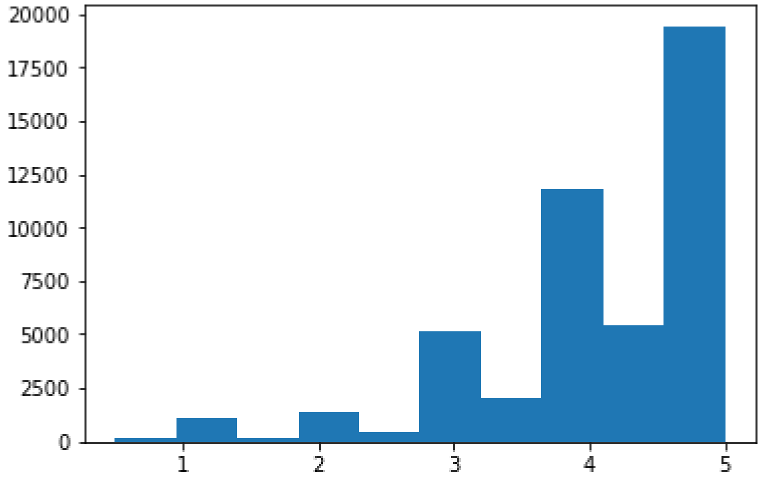
Out[167]:

	rating
cluster	
0.0	4.346774
1.0	4.267327
2.0	3.774834
3.0	3.854032
4.0	4.061798

```
In [168]: avgPulpRating = indexedPulpReviews["rating"].mean()
          avgPulpRating
```

```
Out[168]: 4.1737058811044845
```

```
In [169]: plt.hist(indexedPulpReviews["rating"])
          plt.show()
```



We see that there are some slight differences in the average rating of each cluster compared to the overall rating of this group for Pulp Fiction. Mostly people just like the movie though, and tend to give it 5 star reviews! It's possible that our clusters are not really different with respect to their views on Pulp Fiction, so let's just see what our test data does.

Step 5: Determine where the test users fit in these clusters, predict that their rating for the movie will be the average of their cluster

```
In [170]: TestFilter = ratingsPlus["userId"].isin(testUsers)
          ratingsForTest = ratingsPlus[TestFilter]
          ratingsForTest.head()
```

Out[170]:

	userId	movieId	rating	title	genres
2	13	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
18	142	2	4.0	Jumanji (1995)	Adventure|Children|Fantasy
20	156	2	5.0	Jumanji (1995)	Adventure|Children|Fantasy
26	220	2	3.0	Jumanji (1995)	Adventure|Children|Fantasy
35	278	2	3.5	Jumanji (1995)	Adventure|Children|Fantasy

In [171]:

```
if compute:
    userDicts = []
    userIds = []
    for thisUser in testUsers:
        thisUserDict = {}
        thisUsersRatings = ratingsForTest[ratingsForTest["userId"] == th
isUser]
        for genre in genreList:
            genreFilter = thisUsersRatings["genres"].str.contains(genre)
            avgRating = thisUsersRatings[genreFilter]["rating"].mean()
            thisUserDict[genre]=avgRating
        userDicts.append(thisUserDict)
        userIds.append(thisUser)
    df2 = pd.DataFrame(userDicts, index = userIds)
    df2.to_csv("TestingDf.csv")
else:
    df2= pd.read_csv("TestingDf.csv", index_col = 0)
```

In [172]:

```
df2NoNan=df2.replace(np.nan,0)
df2NoNan.head()
```

Out[172]:

	(no genres listed)	Action	Adventure	Animation	Children	Comedy	Crime	Documen
75429	0.0	3.542857	3.227273	4.200000	3.181818	3.750000	4.136364	5.000000
6624	0.0	2.913953	2.938596	3.600000	3.531250	3.020161	3.235849	2.000000
104782	0.0	3.562500	3.666667	4.333333	4.200000	3.416667	3.333333	0.000000
12073	0.0	3.500000	4.111111	4.250000	4.233333	4.120690	2.423077	0.000000
16075	0.0	3.369822	3.355556	3.636364	3.379310	3.456647	3.694690	3.583333

In [173]:

```
predictions = kmeans.predict(df2NoNan)
```

In [174]:

```
testData = pd.DataFrame()
testData = df2NoNan
testData["cluster"] = predictions#pd.Series(predictions)
```

In [175]:
```
testData.head()
```

Out[175]:

	(no genres listed)	Action	Adventure	Animation	Children	Comedy	Crime	Documen
75429	0.0	3.542857	3.227273	4.200000	3.181818	3.750000	4.136364	5.000000
6624	0.0	2.913953	2.938596	3.600000	3.531250	3.020161	3.235849	2.000000
104782	0.0	3.562500	3.666667	4.333333	4.200000	3.416667	3.333333	0.000000
12073	0.0	3.500000	4.111111	4.250000	4.233333	4.120690	2.423077	0.000000
16075	0.0	3.369822	3.355556	3.636364	3.379310	3.456647	3.694690	3.583333

5 rows × 21 columns

In [176]:
```
testAssignments = pd.DataFrame({"cluster": testData["cluster"]})
#testAssignments.head()
```

In [177]:
```
testAssignments.insert(1,"ratingPredict", testAssignments["cluster"]*0)
```

In [178]:
```
for i in range(len(testAssignments)):
    testAssignments["ratingPredict"].iloc[i]=clusterPulpRatings.loc[test
Assignments["cluster"].iloc[i]]["rating"]
```

```
/anaconda/lib/python3.6/site-packages/pandas/core/indexing.py:179: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  self._setitem_with_indexer(indexer, value)
```

In [179]:
```
testAssignments["userId"]=testAssignments.index
testAssignments.head()
```

Out[179]:

	cluster	ratingPredict	userId
75429	63	4.151144	75429
6624	46	3.463693	6624
104782	18	3.813312	104782
12073	37	3.549724	12073
16075	50	4.292353	16075

Step 6: Compare these predicted ratings vs. their true rating to the default prediction vs. true rating (the default prediction is that all users would rate it as the total average rating for that movie)

In [180]:

```
TestPulpReviews=ratingsForTest[["userId", "rating"]][ratingsForTest["movieId"]==mId]
```

In [181]:

```
testPredictTrue = testAssignments.merge(TestPulpReviews, on="userId")
```

In [182]:

```
testPredictTrue["defaultPredict"]=avgPulpRating
testPredictTrue.head()
```

Out[182]:

	cluster	ratingPredict	userId	rating	defaultPredict
0	46	3.463693	99243	3.0	4.173706
1	64	4.083333	109454	5.0	4.173706
2	28	4.053790	41160	4.5	4.173706
3	2	3.774834	42843	1.0	4.173706
4	70	4.705311	4156	5.0	4.173706

Calculate the root mean squared error:

In [183]:

```
predictScore = np.sqrt(((testPredictTrue["ratingPredict"]-testPredictTrue["rating"])**2).mean())
print(predictScore)
```

```
0.9520186432
```

In [184]:

```
defaultScore = np.sqrt(((testPredictTrue["rating"]-testPredictTrue["defaultPredict"])**2).mean())
print(defaultScore)
```

```
0.981877660684
```

In [185]:

```
print("% improvement: ",(defaultScore-predictScore)/defaultScore*100)
```

```
% improvement:  3.0410119997
```

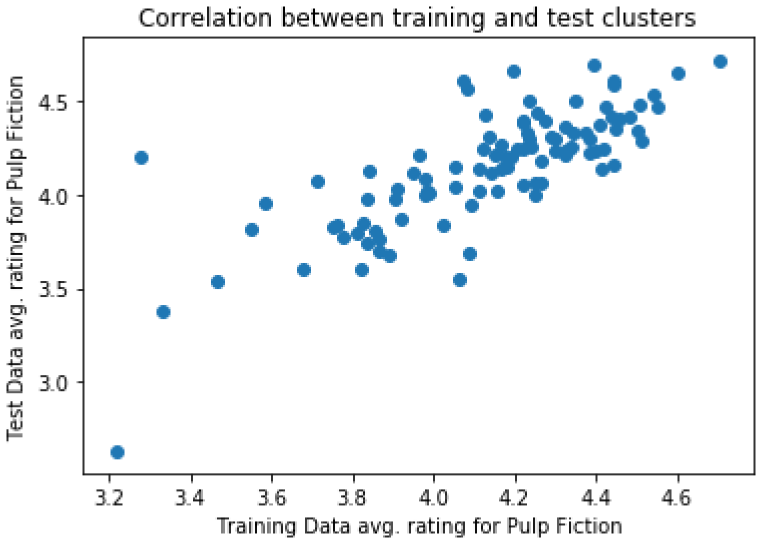
There is a slight improvement in our ability to predict the user's rating for "Pulp Fiction" over the default prediction.

In [186]:
```
clusterTestPulpRatings = testPredictTrue[["rating",
"cluster"]].groupby("cluster").mean()
```

In [187]:
```
TestPulpReviews=ratingsForTest[["userId", "rating"]][ratingsForTest["mov
ieId"]==mId]
```

In [188]:
```
df4 = pd.DataFrame({})
df4["training ratings"] = clusterPulpRatings
df4["test ratings"] = clusterTestPulpRatings
print(df4.head())
print(df4.corr())
plt.scatter(clusterPulpRatings, clusterTestPulpRatings)
plt.title("Correlation between training and test clusters")
plt.xlabel("Training Data avg. rating for Pulp Fiction")
plt.ylabel("Test Data avg. rating for Pulp Fiction")
plt.show()
```

```
   training ratings  test ratings
0          4.346774      4.326087
1          4.267327      4.185039
2          3.774834      3.774306
3          3.854032      3.810924
4          4.061798      3.544118
                  training ratings  test ratings
training ratings          1.000000      0.775352
test ratings              0.775352      1.000000
```



The average rating for Pulp Fiction in each group is well correlated between the training and the test data.

```
In [190]: testPredictTrue.describe()
```

```
Out[190]:
```

	cluster	ratingPredict	userId	rating	defaultPredict
count	6141.000000	6141.000000	6141.000000	6141.000000	6.141000e+03
mean	44.833903	4.169307	69246.877870	4.170901	4.173706e+00
std	29.809134	0.276416	39887.720508	0.981954	2.753577e-13
min	0.000000	3.220395	18.000000	0.500000	4.173706e+00
25%	21.000000	3.983755	35085.000000	4.000000	4.173706e+00
50%	43.000000	4.178105	68240.000000	4.500000	4.173706e+00
75%	70.000000	4.374656	103903.000000	5.000000	4.173706e+00
max	99.000000	4.705311	138473.000000	5.000000	4.173706e+00